Measuring the Effects of Cleantech Investment on Firm Growth using Matching and Difference-in-Differences Methods

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Outline

Objectives

Motivation for the study, program background, and Statistics Canada's business microdata

- Understand that measuring the impact of complex programs always starts with a clear research question and is often achievable with a simple study design.

Difference-in-differences methodology and the importance of matching

- Understand the concepts that underlie difference-in-differences and why matching is important.

Results, conclusion and next steps

- Read and interpret results of quantitative analysis.
- Reflect on ways to improve.

Motivation

- Since the mid-1990s, Canada has given beneficial tax treatment to businesses to encourage investment in clean energy generation and energy conservation technologies.
  - Jordaan et al. (2017) – Investment in clean energy technologies is important for reducing GHG emissions.
- While it is generally accepted that investment is an important driver of macroeconomic growth, relatively little is known about how cleantech investment affects economic performance at the firm level.
  - Bjornalia and Ellingsen (2014): Cleantech and performance literature review that most studies focus on environmental outcomes rather than economic or financial performance.
- The question this study addresses is, do tax incentives to promote business investment in cleantech cause firms to grow faster?

Background: Tax Incentive for Cleantech Investment

- Firms that invest in cleantech can be identified using corporate income tax data.
- As an incentive to invest, the federal tax system allows firms to deduct the cost of many purchased capital assets gradually over the asset's useful life as a capital cost allowance (CCA).
- The cost of some assets, like those classified as cleantech (asset classes 43.1 and 43.2), can be deducted at an accelerated rate.
    - Assets in class 43.1 have an accelerated CCA rate of 30% per year. For assets in class 43.2, a higher efficiency standard is required to have a 50% CCA rate.

Background: Cleantech Assets

- Asset classes 43.1 and 43.2, clean energy technologies in Canada in 2018

- Cogeneration and Specified-Waste Fueled Electrical Generation Systems
- Thermal Waste Electrical Generation Equipment
- Active Solar Heating Equipment and Ground-Source Heat Pump Systems
- Small-Scale Hydro-Electric Installations
- Heat Recovery Equipment
- Wind Energy Conversion Systems
- Photovoltaic Electrical Generation Equipment
- Geothermal Electrical Generation Equipment
- Landfill Gas and Digester Gas Collection Equipment
- Specified-Waste Fueled Heat Production Equipment
- Expansion Engine Systems
- Systems to Convert Biomass into Bio-Oil
- Fixed Location Fuel Cell Equipment
- Systems to Produce Biogas by Anaerobic Digestion
- Wave or Tidal Energy Equipment
- District Energy Systems/Equipment
- Electric Vehicle Charging Infrastructure
- Electrical Energy Storage Property
- Geothermal Heat Generation Equipment

Scott, Elgie and Monahan (2019)

Data

- The data are from Statistics Canada's National Accounts Longitudinal Microdata File (NALMF) derived from corporate income tax data.
- Data for cleantech investment (43.1 and 43.2) were added separately using T2 corporate tax files from Schedule 8 – Capital Cost Allowance (CCA)
    - Cleantech firms are defined as those that purchase assets in classes 43.1 and 43.2 used for producing goods and services and not for resale.
- The analysis used data from 2011 to 2018 for the manufacturing sector.
- Variables of interest
    - Outcomes: employment
    - Covariates (firm characteristics): debt, assets, operating expenses, wages, firm age, R&D investment, labour productivity, employment, and a multi-establishment indicator.

What is Difference-in-Differences (DID)?

- DID is one way to estimate the effects of a program or policy.

- DID compares the differences in an outcomes, like employment or revenues, of businesses that participate in a program and those that do not participate before and after the initial period the program.

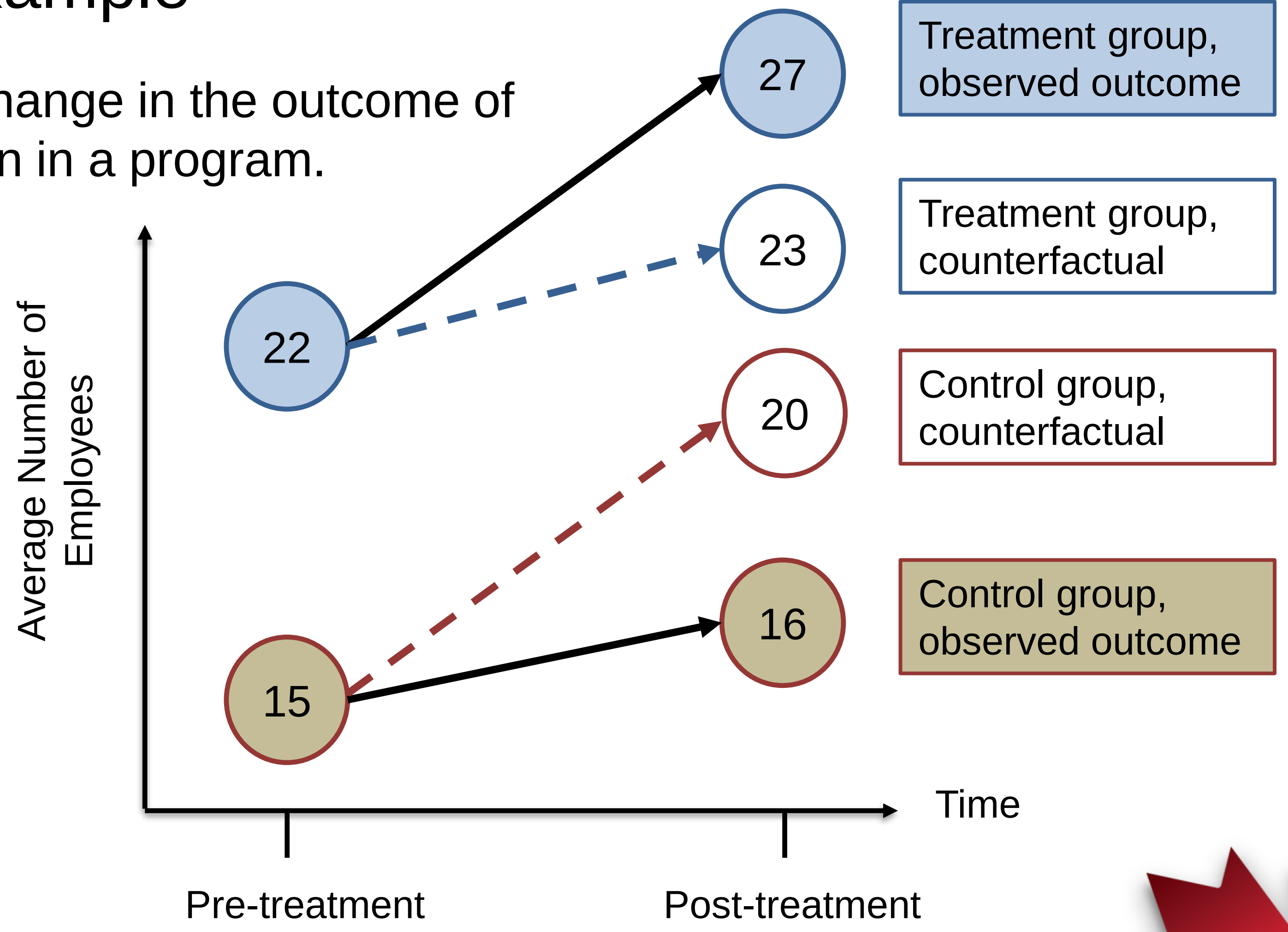
- If the change in the outcome is larger for the participants than for the non-participants, we can argue that the program caused the difference.

Using DID to Estimate the Average Treatment Effect on the Treated (ATT), a Simple Example

- ATT is a measure of the average change in the outcome of businesses due to their participation in a program.

- DID estimates a counterfactual outcome that differs from the treatment groups' actual outcome by an amount that represents ATT.

- With an accurately estimated counterfactual, we can measure the impact of the program on treated firms' outcomes, like employment.



Using DID to Estimate the Average Treatment Effect on the Treated (ATT), a Simple Example

DID estimates the value of the ATT using the following formula

$$ATT = (Y_{(T=1,\ P=1)} - Y_{(T=1,\ P=0)}) - (Y_{(T=0,\ P=1)} - Y_{(T=0,\ P=0)})$$

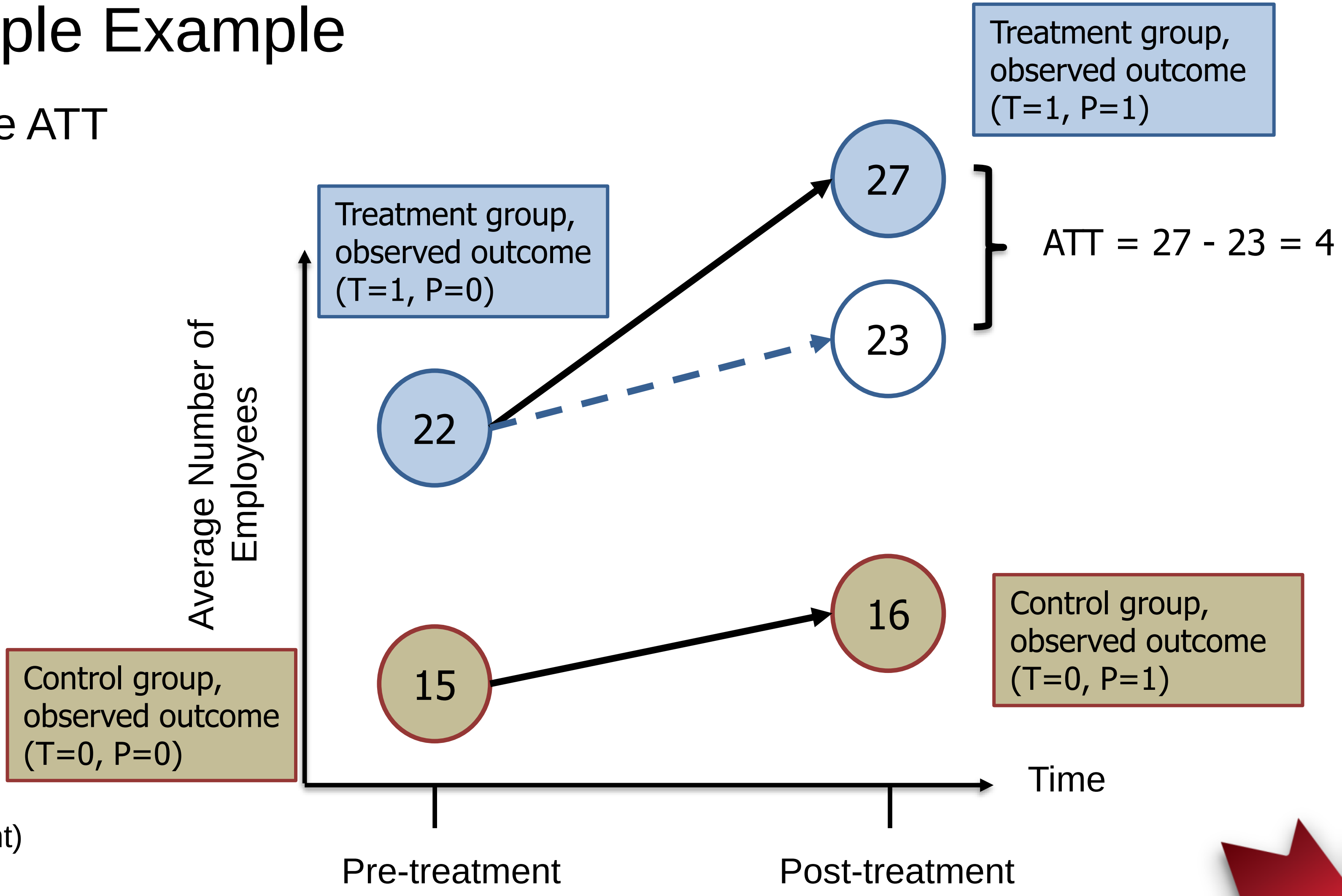
$$ATT = (27 - 22) - (16 - 15)$$

$$ATT = 4$$

Y = outcome variable (employment)

T = treatment (1 = treated, 0 = untreated)

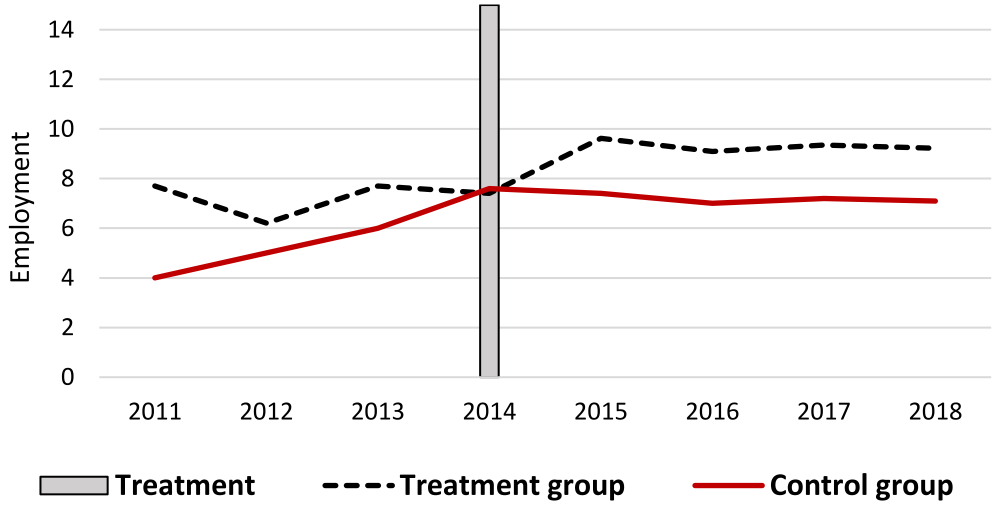
P = post (1 = post-treatment, 0 = pre-treatment)



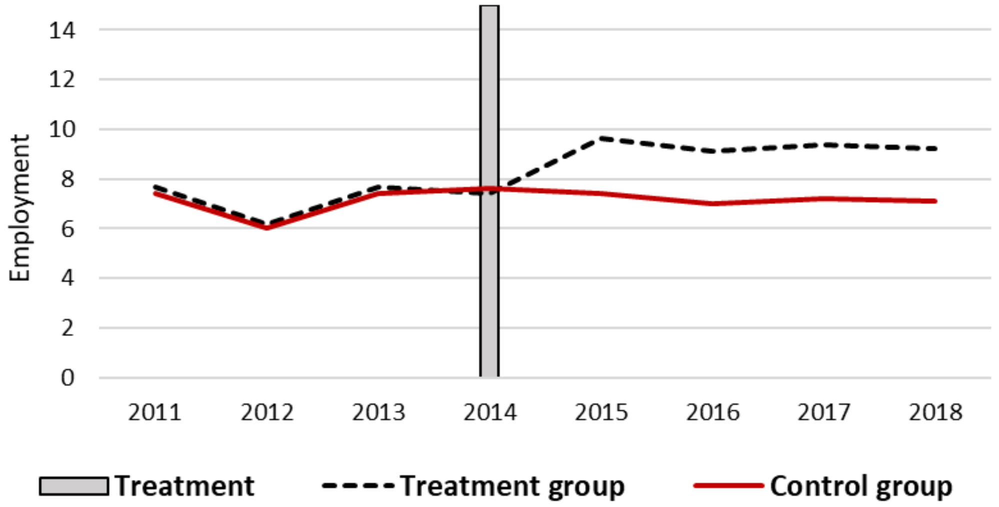
DID Assumptions

- The parallel trends assumption (PTA)
  - For DID to produce valid results it must be true that the outcomes for treated and untreated firms would be the same if both groups received the treatment, or conversely, if both groups did not receive the treatment.
    - In other words, the only thing that should distinguish treated firms from untreated firms is the treatment (participation in the program).
  - If the observed trends in outcomes for both groups are similar before the treatment, we can make a strong argument that the only reason treated firms have different outcomes compared to untreated firms is due to the program, and not differences in firm characteristics, like size, age, etc.

Parallel Trends Assumption (PTA)



PTA is violated



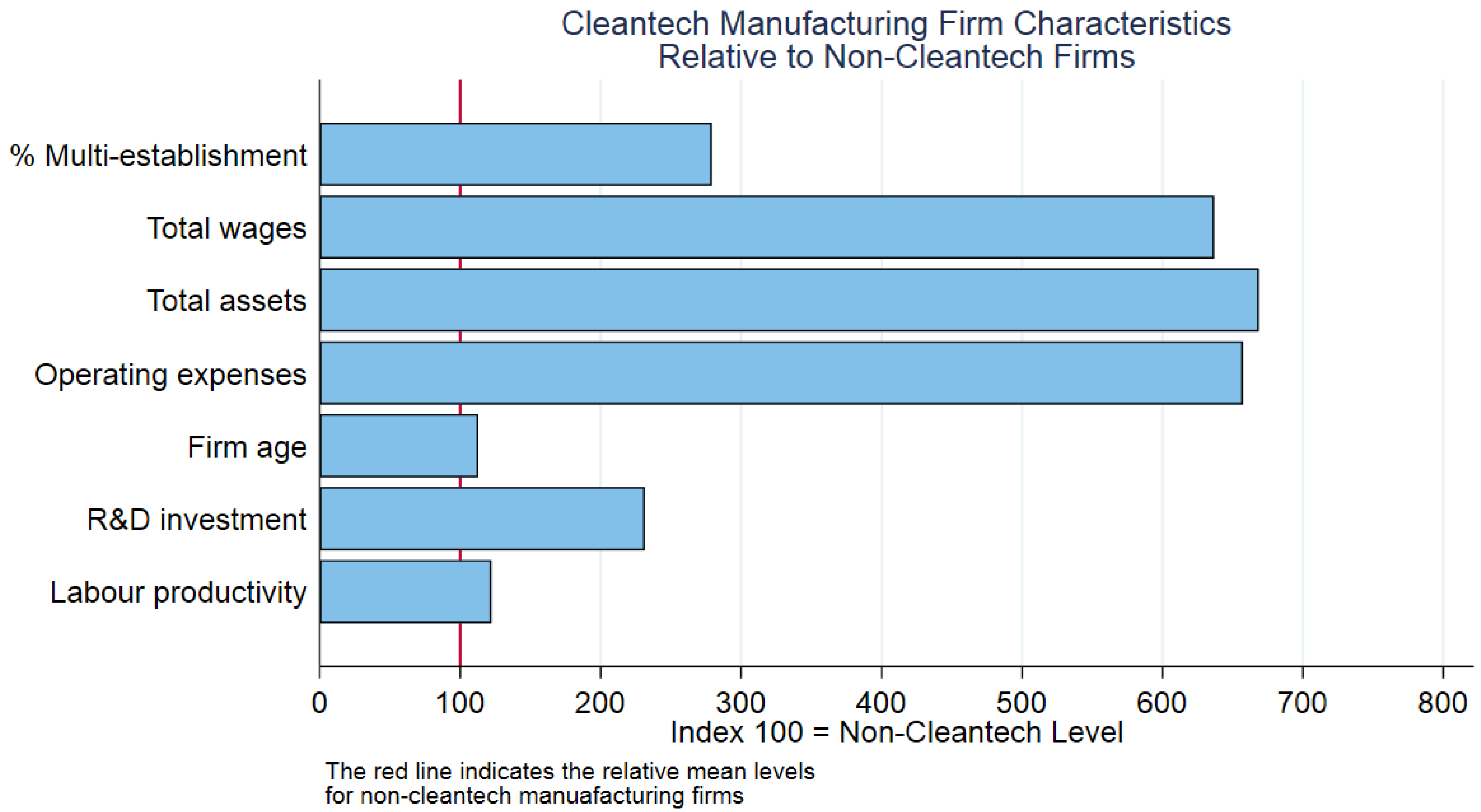
PTA is satisfied

DID Assumptions

- Stable Unit Treatment Value Assumption (SUTVA)
  - SUTVA has two main components:
  - Consistency: The treatment does not vary among firms. In simpler terms, the treatment effect is consistent and uniform for each treated firm.
  - No Interference: The outcome of one firm is unaffected by the treatment status of another firm. Essentially, one firm's treatment should not influence another's outcome.

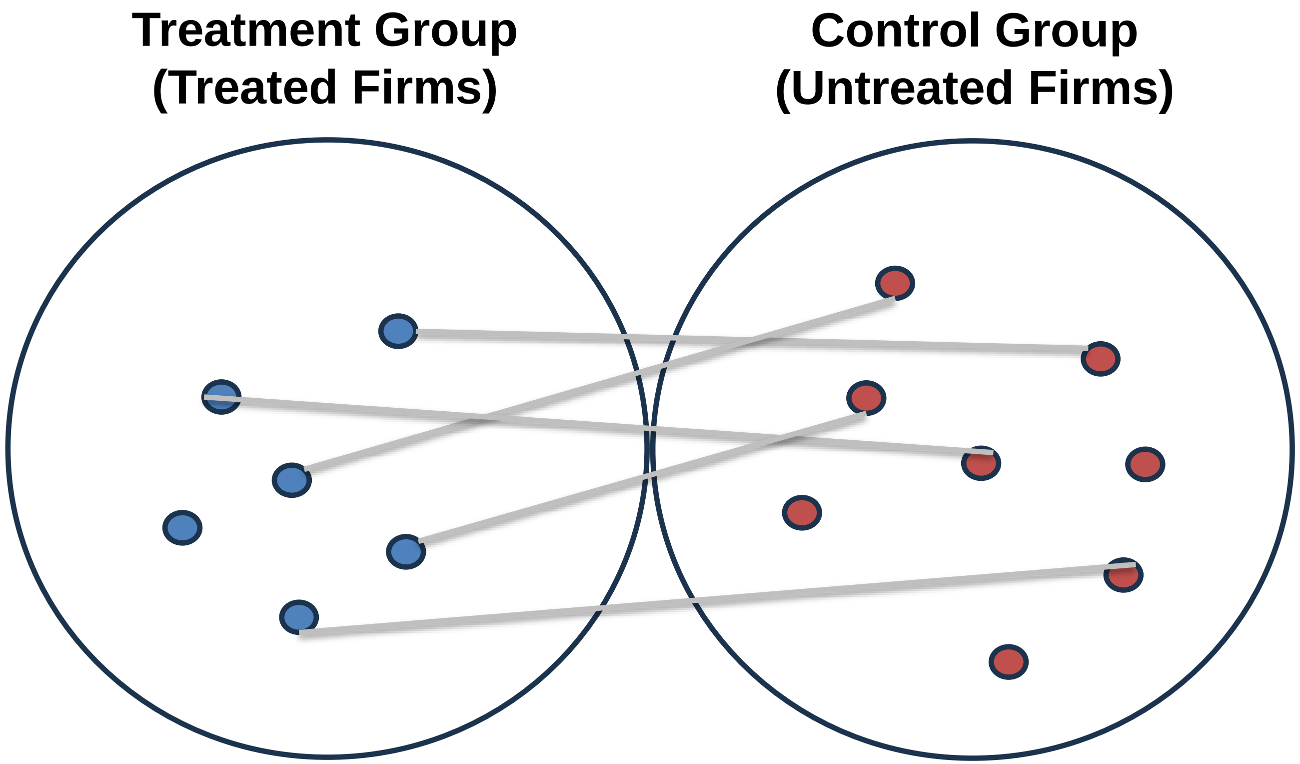
Challenges: Finding a Control Group

- Cleantech firms in manufacturing are large on average.
  - For example, the proportion of cleantech firms in manufacturing with multiple establishments (15%) is nearly three times larger than it is for all non-cleantech firms (5%).
- Total wages, total assets and operating expenses are between six to seven times larger than non-cleantech firms on average.



Matching the Treated and the Untreated

- Propensity score matching (PSM) is a common matching method.
- PSM calculates the probability that firms are treated. It does this for all firms, whether they were actually treated or not, based on the firms' characteristics in the pre-treatment period.
- The objective is for each firm in the treatment group to have one or more corresponding firms with similar characteristics in the control group.
- Selecting untreated firms with the same characteristics as treated firms into the control group reduces the possibility that differences between the outcomes of treated and untreated firms can be attributed to differences in firms' characteristics instead of the treatment.



Challenges: Covariate Balance

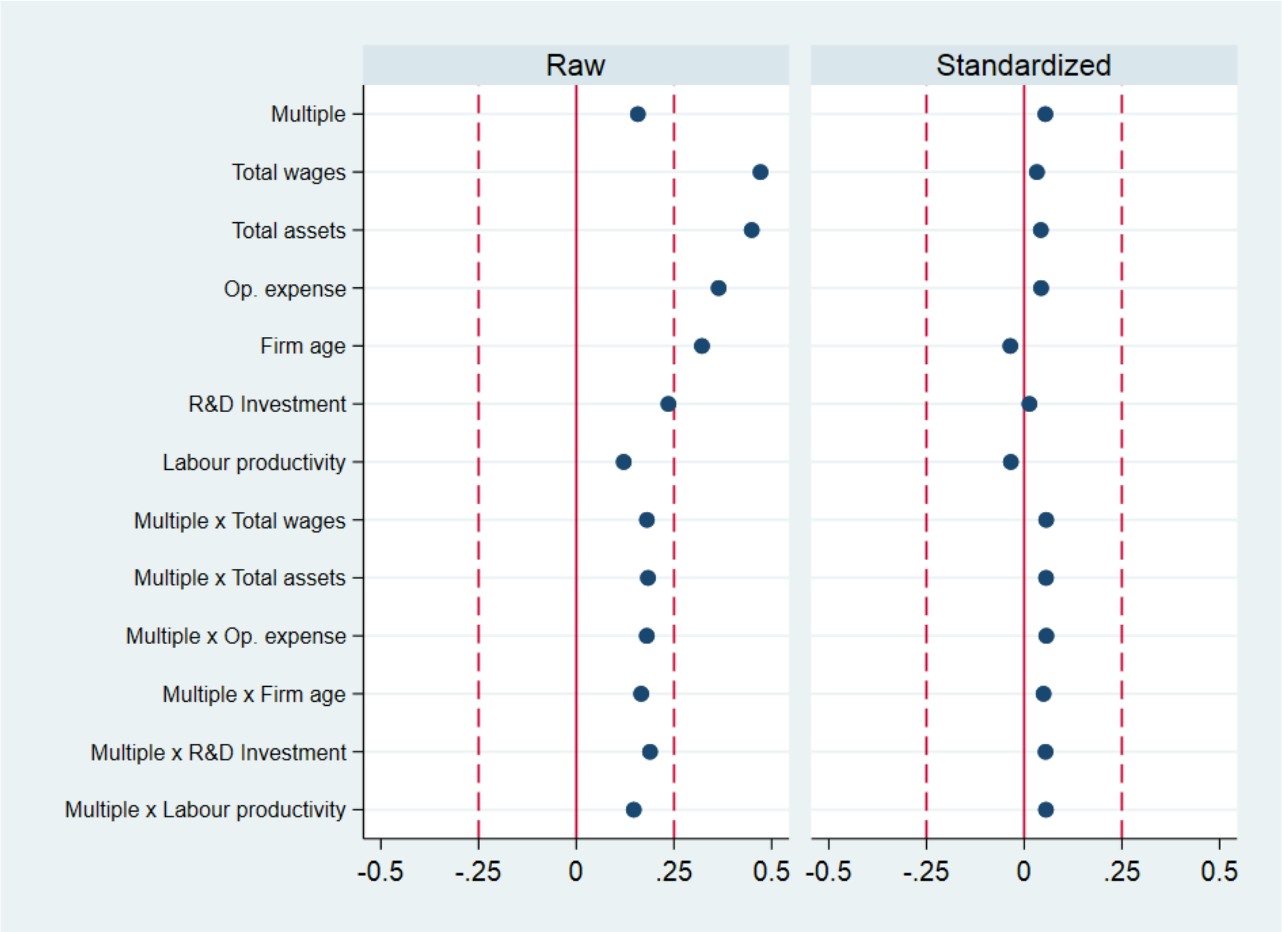
- The mean values of characteristics for firms before matching (raw) may be very different.
- The means after matching (standardized) firms in the treatment and control groups should be much closer.

Table 1: Means and Standardized Differences of Variables used for Matching Treatment and Control Groups: A Hypothetical Example

Covariate Name	Raw Treated	Raw Untreated	Raw StdDif	Matched Treated	Matched Untreated	Matched StdDif
% Multi-establishment	3.49	1.16	2.33	3.49	3.90	-0.41
Total wages	16.30	2.63	13.67	16.30	15.88	0.42
Total assets	54.75	8.17	46.58	54.75	53.25	1.50
Operating expenses	20.73	3.19	17.54	20.73	19.83	0.90
Firm age	10.70	9.73	0.97	10.70	11.16	-0.46
R&D investment	4.95	2.25	2.70	4.95	5.01	-0.06
Labour productivity	12.05	10.04	0.23	12.05	12.29	-0.24

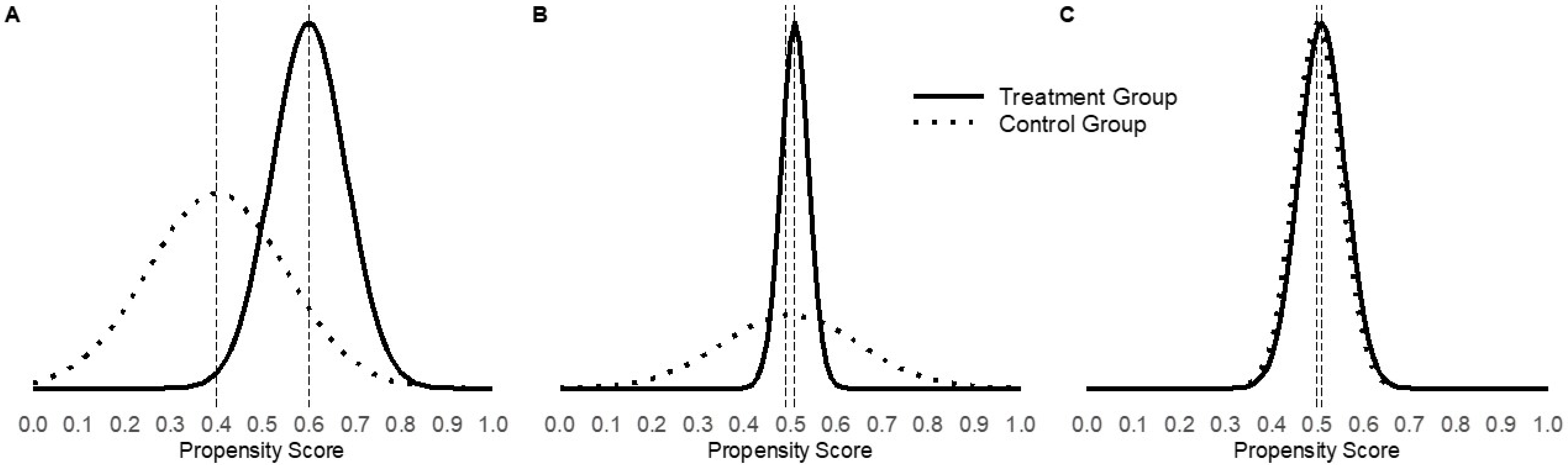
Challenges: Covariate Balance

Means



- Another way to represent the same information, commonly found in impact studies is a graph showing differences in the standardized means for treated and untreated firms.
- Acceptable values for the percentage standardized bias for means should be between -25% and 25%.
- A value of 0% would suggest no imbalance for individual covariates and for the covariates overall.

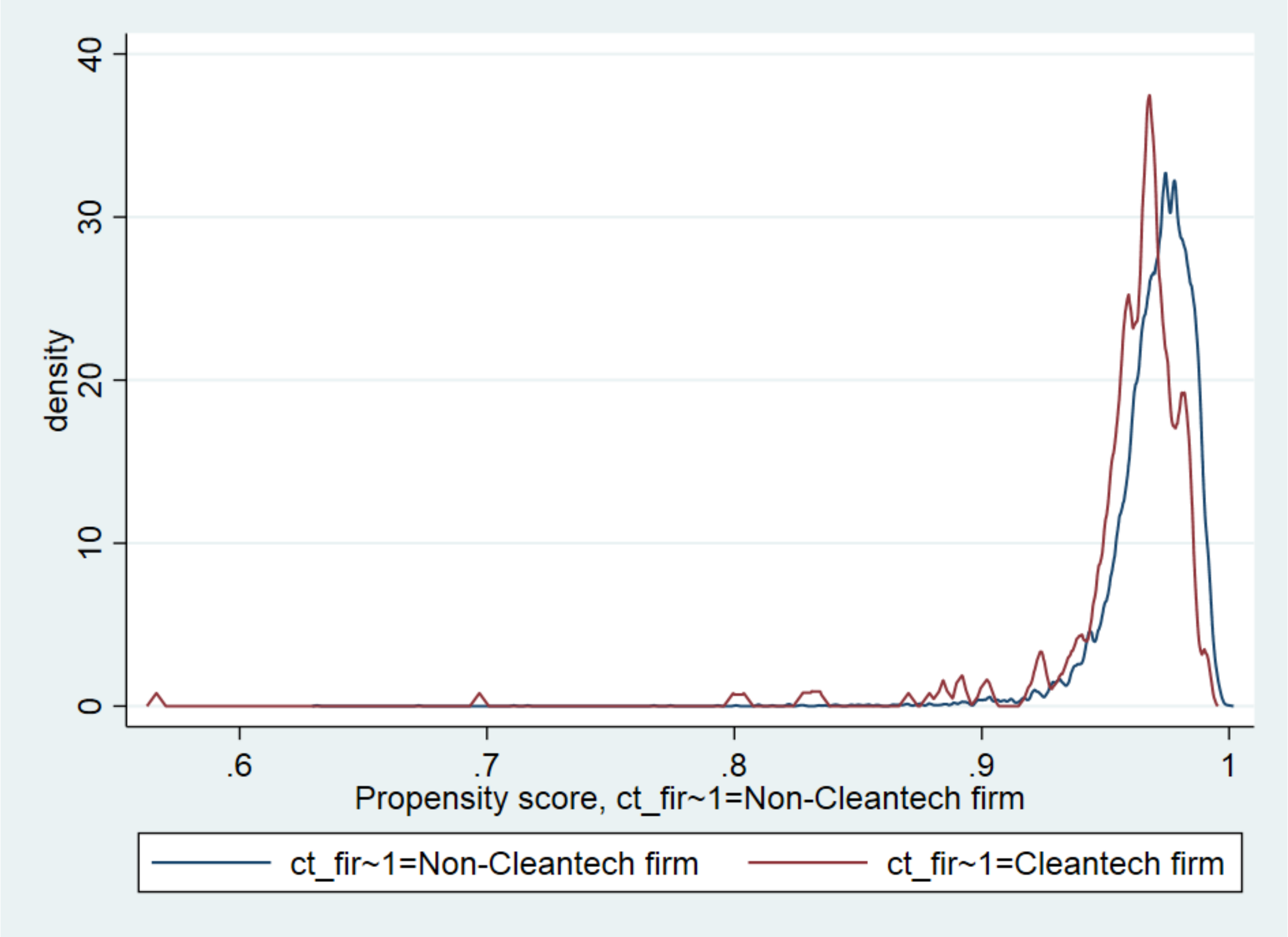
Challenges: Covariance Balance and Overlap



(A) Two distributions with poor balance and overlap; (B) two distributions with good balance but poor overlap; (C) two distributions with good balance and overlap represent well matched control and treatment groups.

Challenges: Overlap

- The matched treatment and control groups have similar distributions.
- Two-sample Kolmogorov-Smirnov test for equality of distribution functions.
- The null hypothesis that the treatment and control samples have the same distribution was not rejected.



Methodology: DID

- (1) is a more formal representation of the first simple example on slides 9 and 10, that is commonly found in impact studies.

- (2) is a regression equation, also found in most studies. It produces the same results as (1) in the simple example, but it also allows analysts to evaluate the level of confidence in their estimate of ATT.

$$ATT = \{\mathbb{E}[Y_{(P=1)}|T=1] - \mathbb{E}[Y_{(P=0)}|T=1]\} - \{\mathbb{E}[Y_{(P=1)}|T=0] - \mathbb{E}[Y_{(P=0)}|T=0]\} \quad (1)$$

$$Y = \beta_0 + \beta_1 \times T + \beta_2 \times P + \beta_3 \times (T \times P) + \varepsilon \quad (2)$$

- *Y* is employment.
- *T* is the treatment indicator (1 = treated, 0 = untreated).
- *P* represents the post-treatment period indicator (1 = post-treatment, 0 = pre-treatment).
- β_0 is called the intercept, it measures firms' mean employment for the control group in the pre-treatment period (*T*, *P* = 0).
- β_1 captures the difference in mean outcomes between the treatment and control groups.
- β_2 captures the difference in mean outcomes between the pre-treatment and post-treatment periods.
- β_3 measures ATT, it represents the additional effect of the treatment in the post-treatment period, above and beyond any group effects captured by $\beta_1$or time effects captured by β_2.
- ε is the error term, it measures the variation in employment not explained by the intercept or explanatory variables.

An Example Dataset

- A visual examination helps to confirm that the data are consistent with the analytical approach.
  - T = 0 all years for the control group and T = 1 all years for the treatment group.
  - P = 0 all firms from 2011-2014 and P = 1 all years from 2015 to 2018.
    - P = 1 in 2014 would suggest that the analyst believes there is some possibility that the treatment could have an immediate impact.
  - TxP = 1 for treated firms in the post-treatment period, and TxP = 0 otherwise.

Obs	Firm ID	Year	Employment	Treated	Post	Treated x Post
1	1	2011	7.4	0	0	0
2	1	2012	6.0	0	0	0
3	1	2013	7.4	0	0	0
4	1	2014	7.6	0	0	0
5	1	2015	7.4	0	1	0
6	1	2016	7.0	0	1	0
7	1	2017	7.2	0	1	0
8	1	2018	7.1	0	1	0
9	2	2011	7.7	1	0	0
10	2	2012	6.2	1	0	0
11	2	2013	7.7	1	0	0
12	2	2014	7.4	1	0	0
13	2	2015	9.6	1	1	1
14	2	2016	9.1	1	1	1
15	2	2017	9.4	1	1	1
16	2	2018	9.2	1	1	1

Results: Employment Growth

The Impact of Cleantech Investment in 2014 by Manufacturers on Employment from 2014 - 2018

	(1) 2014	(2) 2015	(3) 2016	(4) 2017	(5) 2018
Cleantech Investment	0.010	0.009	0.008	0.004	-0.006
(Treated x Post)	(0.222)	(0.299)	(0.411)	(0.642)	(0.493)
Treated	-0.002	0.001	0.001	0.001	-0.000
	(0.285)	(0.508)	(0.648)	(0.681)	(0.788)
Post	0.005	0.005	-0.001	-0.003	0.001
	(0.065)	(0.081)	(0.669)	(0.357)	(0.709)
Constant	-0.021	-0.048	0.008	0.044	0.019
	(0.551)	(0.087)	(0.795)	(0.352)	(0.643)
Observations	11454	11024	10712	10309	9974
Adjusted R^2	0.007	0.006	0.001	0.002	0.000

Dependent variable is employment growth in the year corresponding to the model year.
p-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Conclusions

- The objectives of tax incentives under the CCA regime is to encourage clean energy generation and conservation, not necessarily economic growth.

- Used business microdata in a DiD framework to assess the impact on firm growth due to investing in cleantech.

- The results suggest that firms making an initial cleantech investment (asset class 43.1 and 43.2) in 2014 did not have higher employment than the comparable control group.

Next Steps

- Refine methodology to include multiple treatment periods and differing treatment types (asset classes 43.1 and 43.2).
  - Examine specific technologies.
- More complex treatment indicator to capture variation in treatment intensity among firms.
- Different methodology to capture differences in treatment intensity among firms.

Resources for Learning Causal Inference Methods for Quantitative Impact Analysis

- Andrew Heiss, Program Evaluation for Public Service, https://evalsp20.classes.andrewheiss.com/

- Joshua Angrist and Jörn-Steffen Pischke, Mastering Metrics: https://www.masteringmetrics.com/

- Scott Cunningham, Causal Inference: The Mixtape: https://mixtape.scunning.com/

- Matheus Facure, Causal Inference for the Brave and True: https://matheusfacure.github.io/python-causality-handbook/landing-page.html#contribute

- Miguel Hernan, Causal Inference: What If (the book): https://www.hsph.harvard.edu/miguel-hernan/causal-inference-book/

Thank you

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